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Małgorzata Pawłowska https://orcid.org/0000-0002-2715-5446

prof. dr hab., Szkoła Główna Handlowa w Warszawie, Al. Niepodległości 162,02-554 Warsaw

e-mail: mpawlo1@sgh.waw.pl

FINTECH, ARTIFICIAL INTELLIGENCE, FINANCIAL RISK AND MACRO-FINANCIAL LINKAGES

ABSTRACT

The purpose of the article. The aim of this paper is to determine the impact of FinTech and Artificial Intelligence (AI) on the relationship between the financial sector and the real economy through the channel of credit. Furthermore, digital technologies, including artificial intelligence, adopted by traditional banks contribute to reshaping the dynamics of financial risk.

Methodology. In the first part, a critical analysis of the literature was conducted. Part Two presents a quantitative research including a panel data analysis based on data from European countries concerning traditional credit and FinTech credit.

Results of the research. A critical analysis of the literature confirms the significant impact of digital technologies on financial products and financial risk. Moreover, a quantitative research indicates the considerable influence of new technologies on the relationship between the financial sector and the real economy. The results suggest that, in European countries, FinTech credit tends to be a substitute for traditional bank credit for households and that AI supports the development of the FinTech credit market in these countries.

Keywords: digital technologies, FinTech credit, AI, financial risk, bank credit, macro-financial linkages

JEL Class: G21, F36, G2, G21, G34

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Introduction

After the global financial crisis of 2008, digital solutions were implemented at a rapid pace to match financial products better to customer needs. New enterprises, known as FinTechs, which are not traditional banks, have emerged in the financial sector. FinTech companies encompass various financial innovations, such as crowdfunding platforms, blockchain, and mobile payment platforms, which have transformed the world of finance and the methods of financing economic entities (FSB, 2024). The basic banking product that connects the financial sector and the real economy is credit. FinTech companies, like banks, can provide credit and loans. At the same time, we are observing an increase in the use of artificial intelligence (AI) in the financial sector (Boobier, 2020; Aldasoro, et. al., 2024; FSB, 2024). Therefore, in this paper, the concept of macro-financial linkages refers to the interaction between the real economy and the financial sector through the credit channel, as well as the role of digitalization in the growth of credit market. The wider use of FinTech and AI in finance has brought transformative benefits to the financial sector but may also exacerbate existing risks (Cornelli et al., 2023; Acharya et al, 2024). Furthermore, by entering the area of activity previously reserved for banks, FinTech companies exert a huge impact on competition in the financial services sector and credit bank market (Pawłowska, 2023).

The aim of this paper is to determine the impact of digital technologies, including Artificial Intelligence (AI), on the relationship between the financial sector and the real economy. Part One, within the framework of a literature review, defines the channels through which new technologies and AI impact traditional banking, lending market, financial risk and real economy. Part Two presents the quantitative method applied for the analyzed role of FinTech credit in European economy. Despite the relevance of the topic, empirical work in this field concerning Europe remains quite scarce. The paper fills a research gap in research on the relationship between the financial sector and the real economy due to digitalization and AI in European banking sector. Similar studies for the global economy were provided by Claessens et al. (2018), based on a simple cross-sectional analysis, and by Cornelli et al. (2023), based on global panel data. The originality of this study lies in the use of a panel regression model for panel data constructed for selected European countries. Furthermore, this paper also examined the relationship between FinTech credit and total credit, divided into credit for households and for corporate clients. Additionally, the research incorporates AI-related variables.

This paper consists of four chapters and a conclusion. The first chapter presents motivation, research questions and hypotheses. The second chapter includes the basic definitions. The third chapter discusses the impact of digitalization and artificial intelligence on the financial sector. The fourth chapter describes the model based on the literature. Finally, the conclusion summarizes the research.

1. Research Questions and Hypotheses

The motivation of this paper is complex and is based on the following phenomena affecting traditional finance: digitalization, FinTech, Artificial Intelligence (AI) and macro-financial linkages. Due to the role of traditional banks in the economy, these phenomena affect their financing and the development of macroprudential policy. The 2008 financial crisis confirmed that deepening knowledge on the relations between the financial sector and real economy was critical (cf. Acharya & Richardson, 2009). Similarly, we have observed the impact of digitalization on financial risk.

It should be noted that FinTech companies provide consumer loans, corporate loans, and mortgage loans (Cornelli et al., 2023; Acharya et al., 2024). Traditional banks aiming to make relations with their customers used to be considered a factor lessening information asymmetry (Stiglitz & Weiss, 1981). Furthermore, when banks tighten credit supply due i.e., economic downturns or risk aversion, FinTech lenders may fill this gap, particularly for underserved segments (Buchak et al., 2018; Cornelli et al., 2023). FinTech companies have a comparative advantage with respect to Big Data using platforms that enable the immediate use of matching lenders and borrowers (i.e., the increasing use of the Internet and platforms has made it possible to match lenders and borrowers directly through peer-to-peer (P2P) lending. Moreover, according to literature a FinTech loan can seem to be a supplement (Tang, 2019) or a substitute for a bank loan (Gopal & Schnabl, 2020). Furthermore, Gamborta et al. (2025) found that AI investments help banks mitigate the typical countercyclical effects of relationship lending on firms' credit supply, as well as on their investment and employment decisions.

When examining the influence of digitalization on the loan market, it should be stressed that the role of large technological companies (BigTechs) is significant (BIS, 2019). BigTech companies operate across multiple business lines, with their core activities typically being non-financial, while lending often constitutes only a small part of their operations. Notably, technology giants such as Amazon, Apple, and Google, which already participate in the lending market, possess significant potential for expanding financial services due to their access to vast amounts of customer data (BIS, 2020). Cornelli, et al. (2023), using a global database of FinTech and BigTech lending volumes for 79 countries over 2013–2018 and applying panel regression analysis, found that these alternative forms of credit are more developed in countries with greater ease of doing business and more advanced bond and equity markets. Furthermore, they concluded that FinTech and BigTech credit tend to complement rather than substitute traditional forms of credit.

Building on these findings, this paper focuses on European countries, primarily within the EU, and additionally examines the role of Artificial Intelligence (AI). The aim of this paper is to answer the following main research question: What is the impact of FinTech and AI on lending markets in European countries?

The following research hypotheses were formulated based on the above question:

H1: Digitalization has an impact on financial risk and traditional banks' performance.

H2: FinTech credit is a substitute for bank credit in European countries.

In case to verify research hypotheses, the empirical model has been contacted based on panel data. Data for individual European countries was obtained from publicly available online databases of international organizations, such as the World Bank, Bank of International Settlement, International Monetary Fund, European Central Bank (Statistical Data Warehouse), Eurostat. Data concerning credit comes from the European Credit Research Institute (ECRI) at the Centre for European Policy Studies (CEPS). Panel data concerning FinTech and FinTech credit was based on data from the papers: Cornelli et al., 2020 and Cornelli et al., 2021.

2. Basic Definitions

The financial sector is changing at a very fast pace, which is largely due to the development of digital technologies. To maintain their market position, traditional banks, which have so far only offered services in physical branches, are now implementing information technology (IT) and Big Data (cf. Nayernia et al., 2022). On the other hand, banks and other financial intermediaries invest in the development of modern technologies, which leads to further technical progress. At the same time, we are observing an increase in the use of Artificial Intelligence (AI) in the banking sector (cf. Boobier, 2020; Nicoletti, 2017).

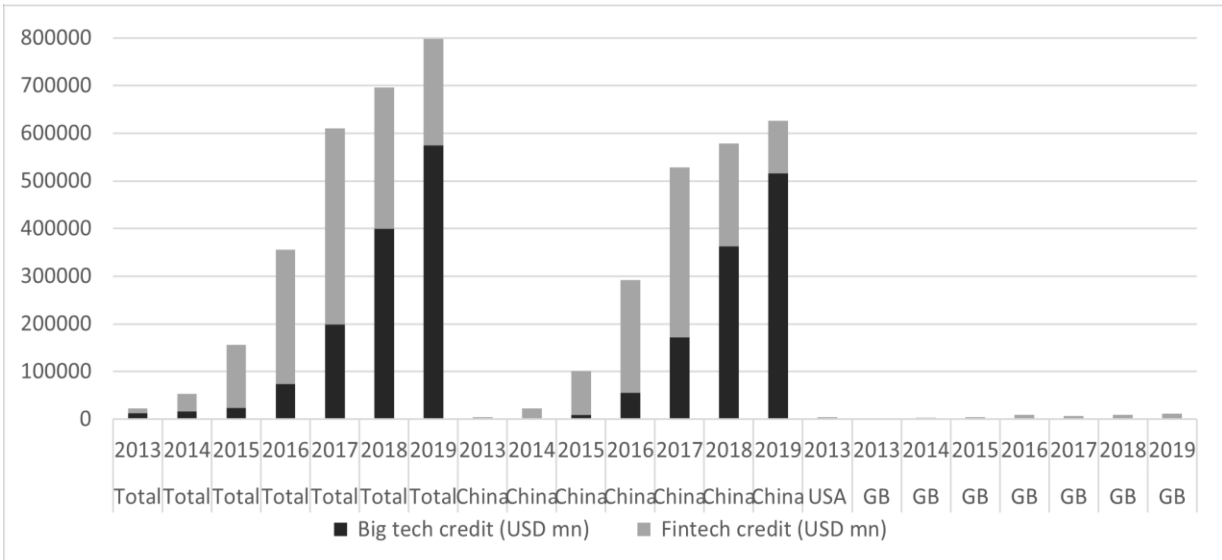
2.1. FinTech: basic definitions

FinTech refers to the integration of digital technology with financial services. FinTech companies filled the existing gaps in the needs of financial service users, which were not met by traditional banks (i.e., speed of service, lower costs, transparency, quick access and security). There is no uniform market definition of FinTech. It is defined by the services and products it co-creates. As the functionality of FinTech-enabled solutions increases, its definition expands. One of the first definitions of FinTech was included in the report of Financial Stability Board (FSB, 2017). This definition presents FinTech as a: "…financial innovation that could result in new business models, applications, processes, or products with an associated material effect on financial markets and institutions and the provision of financial services". Thakor (2020) defined FinTech as "…part of the process of evolving financial innovation, which has theoretically been shown to be risky but of value, with supporting recent evidence that it yields substantial value to investors" (e.g., Thakor, 2020).

FinTech companies range from small startups to large technology firms (BigTech), whose role in transforming financial services traditionally dominated by banks has been increasing (Scardovi, 2017; Beaumont, 2020; Boobier, 2020; Boot et al., 2021; Sironi 2022). One of the concepts related to the functioning of FinTech companies is FinTech credit (Cornelli & Nicoletti, 2017; Fiore et al., 2023; Acharya et al., 2024). FinTech companies like traditional banks provide consumer loans, corporate loans, and mortgage loans. Claessens et al. (2018) found that loans granted by FinTech are growing rapidly, although they are still small compared to loans granted by traditional intermediaries. FinTech credit broadly includes all credit activity facilitated by non-bank electronic (online) platforms. It may also include credit services provided by large tech firms via their platforms. The provision of loans by the FinTech sector enables a wider access to financing. This approach is in line with the position of the FSB (CGFS-FSB, 2017). However, FinTech companies, firstly, have access to a wider group of customers than traditional banks, and secondly, they provide their customers with additional benefits such as greater convenience in using financial services and, moreover, at lower costs. In addition, players from the BigTech sector offer financial services as part of a much wider set of activities, have a high growth potential and can be great competition for traditional commercial banks (cf. Vivies, 2017, p. 101). The FinTech term refers to enterprises using technological innovations in financial services, while large technology companies (BigTechs) offer financial services as part of their activities, which have a much wider scope (BIS, 2019). Furthermore, the development of artificial intelligence (AI) and its use in the financial system have increased the potential for greater efficiency and profits for FinTech and BigTech companies, as well as traditional banks. Notably, technological giants such as Amazon, Apple and Google, which already operate in the lending market, have a great potential for the development of financial services because they have access to a huge amount of customer data (BIS, 2020, p. 7). Traditional banks collect information on customer credit histories over a long period of time, while BigTech companies can use their advantage on the lending market thanks to non-financial data about their customers and can use this data on a much larger scale in their financial activities (BIS Annual Economic Report, 2019, p. 63; BIS, 2020). Due to the broad definition of FinTech loans, compiling aggregate data is challenging, especially since the time series covering this phenomenon is quite short. Initial estimates based on this data were published in Claessens et al. (2018) and Crisanto et al. (2021). It should be noted that FinTech and BigTech credit dominated mainly in China, USA, Japan, Korea, and the UK (see Figure 1). Although the volume of loans issued by FinTech companies is growing rapidly, it remains relatively small compared to that of traditional financial intermediaries (Claessens et al., 2018).

Figure 1

FinTech and BigTech credit (USD mn)



Source: Own elaboration based on: Cornelli et al., 2020.

In Europe, traditional banks still dominate the financial sector; however, banks are increasingly investing in new technologies and adopting additional distribution channels. Furthermore, traditional commercial banks face competition in the lending market also from new players – the so-called neobanks. Neobanks are financial institutions that may have a banking license, but do not have traditional branches, because they use, inter alia, cloud infrastructure to function better on online, mobile and social platforms. They can obtain banking licenses under the existing regulatory regimes, and it is mainly them who can grant loans, create relationships with customers or have traditional banks as business partners (BCBS, 2018).

2.2. AI: basic definitions

Artificial intelligence (Artificial Intelligence, AI) refers to machines that can think, learn, and make decisions like humans and are broadly defined in the past as computer systems that perform tasks that typically require human intelligence (Turing, 1948, 1950; Russell & Norvig, 2010). However, the concept of AI is broad and changes over time, along with technological advancements. Moreover, distinctions are made between the concepts of artificial intelligence or generative artificial intelligence (GenAI). Currently, under the AI term, there are many concepts including neural networks, robotics, machine learning (ML), and deep machine learning (Aldasoro et al., 2024). Another element is natural language processing (NLP), which is a field of artificial intelligence (AI) that makes human language understandable to machines. Computer Vision (CV) is a field of science and technology that focuses on enabling computers to achieve a high level of understanding of digital images and videos.

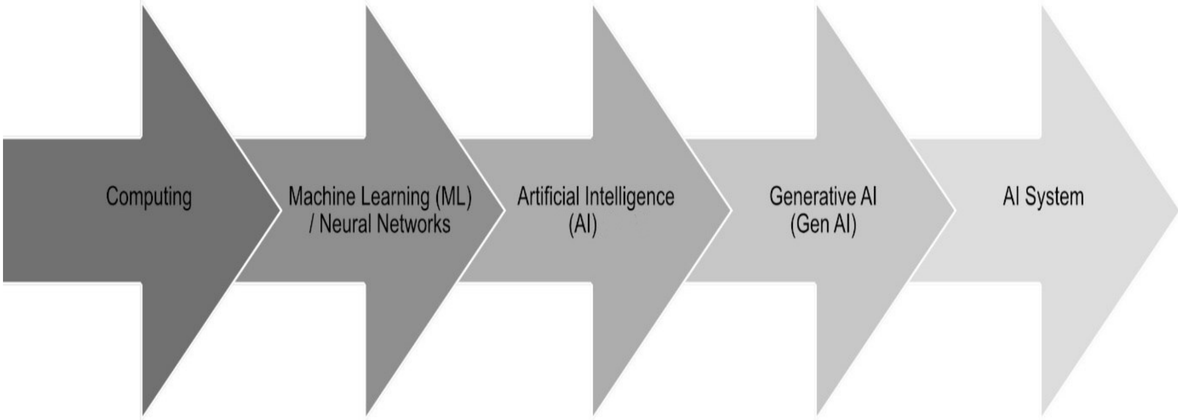
It should be noted that the history of AI is quite long, dating back to the 1930s, when the first works on mathematical logic by Alan Turing (1936) and Kurt Gödel (1931) emerged, which are considered the foundations of AI. In 1955, John McCarthy introduced the term of artificial intelligence to science, defining it as "the science and engineering of making intelligent machines". The following year, in 1956, he organized a scientific conference at Dartmouth titled Dartmouth Summer Research Project on Artificial Intelligence. This event is considered in the scientific community as the birthplace of the field of science called "artificial intelligence" (see IAPP, 2023). Furthermore, Marvin Lee Minsky constructed the first neural network in 1950, contributing to the development of "artificial intelligence". For much of the 20th century, AI was using neural network and expert systems that were developed. While highly useful for basic financial functions (e.g., risk management, basic algorithmic trading rules and credit scoring, fraud detection), they were far from human-level abilities in pattern recognition, handling uncertainty and complex reasoning (Ceruzzi, 2003).

Another impulse for the development of AI has been the emergence of so-called large language models (LLMs), which can, among other things, answer ambiguous questions or analyze the sentiment of texts depending on the context. Large language models (LLMs), a type of generative artificial intelligence (GenAI), are being used as information points and as a way to simplify data analysis and reporting on the basis of the firm's data.

An attempt to identify the definition of AI and AI systems has been made by the OECD (2024a, p. 4). An AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. The definition of AI is contained in the AI principles (Russell & Norvig, 2009; OECD, 2019). However, in an earlier study (OECD, 2023), the OECD attempted to distinguish between the so-called old AI and generative artificial intelligence GenAI (cf. Figure 2).

Figure 2

Development of AI



Source: Own elaboration based on Aldasoro, Gambacorta, Korinek, Shreeti & Stein (2024).

3. The Impact of Digitalization and Artificial Intelligence on financial sector

3.1. FinTech and financial risk

The development of digital technologies has brought innovative changes in the whole financial sector. Additionally, FinTech companies, due to their presence in the credit market, create new challenges and risks and have an impact on macro-financial linkages (Cornelli et al., 2023; Acharya et al., 2024). On the one hand, digitalization has brought benefits to the financial sector. On the other hand, the wider use of FinTech and AI in finance has, but may also exacerbate existing financial risks. Financial risk is a broad concept that includes many types of risks: credit risk, liquidity risk, and operational risk. Generally, financial risk is the possibility of losing money on an investment or a business venture.

Risks associated with the operations of FinTech and Big Tech may be classified at a micro- and macroeconomic level. Microeconomic risks involve, directly or indirectly, possible losses brought on by a loss of funds from financial institutions at the same time due to operational risk, e.g., because of a cyberattack, due to risk inherent in sharing infrastructure, such as cloud services, or due to infractions or failures on account of new solutions that have not been tested yet. Operational risk is on the part of service providers being third persons. External service providers for financial institutions soon grow ever more visible and critical, especially in so-called cloud computing and data services. Since many third-party service providers can cross regulatory limits, greater attention is being shifted to the management of combined operational risks, which may weaken financial stability. Also, transaction risk is on the cryptocurrency market. It is necessary to examine the implications of alternative digital currency configurations for domestic financial systems and the global monetary framework (FSB, 2017).

Macroeconomic risks chiefly pertain to a systemic risk. Systemic risks are of high significance for the macroprudential policy, and they affect the relations between the financial sector and the real economy (FSB, 2017). Systemic risks address the effects of contagion, pro-cyclicality and increasing volatility (Danielsson et al., 2022). Another risk source may arrive along with so-called systemically important institutions. Although cyber risk does not only threaten FinTech, the higher the reliance on digital solutions, but the more access points for hackers also looking for a weak link in the network. BigTechs provide their financial services either competing with the traditional financial institutions or in cooperation, as an overlay on their products and infrastructure. Another risk source may arrive along with so-called systemically important institutions and relates to BigTech companies.

Macro financial risk is connected with pro-cyclicality of FinTech loans. The pro-cyclicality may arise from several sources, including greater concentration in certain market segments (Danielsson et al., 2022). Any assessment of FinTech influence on financial stability, however, is undermined by restricted access of both official, as well as privately disclosed FinTech data. Also, the pro-cyclicality of FinTech loans may arise from financial flows becoming large and unstable i.e. on FinTech credit platforms.

It must be noted that the threats and opportunities from Big Tech affect banking operations differently than those from FinTech (cf. Tanda & Schena, 2019, p. 47). Additionally, BigTechs are actively partnering with and investing in AI startups. Large BigTech companies are leveraging their market power in other markets related to digital technologies and expanding it into emerging artificial intelligence markets. Large tech companies are also heavily investing in artificial intelligence, such as Microsoft's investment in OpenAI (cf. Aldasoro et al., 2024; Gambacorta & Shreeti, 2025).

3.2. AI on Financial Market

In the current decade, the development of AI accelerated. The use of AI is becoming increasingly interesting for entities in the financial system, seeing in it the potential for increased efficiency and profits. Financial institutions are investing heavily in adopting and implementing AI within their organizations. Traditional banks use AI to improve their services (see FSB, 2019, pp. 3–4). The large spending suggests that financial institutions are expecting to benefit significantly from their AI investments (FSB, 2024).

It should be noted that financial institutions have been using artificial intelligence (AI) for many years, and the risks related to AI are known and managed (FSB, 2024). As an example, of using AI in the banking sector one can give customer support chatbots; fraud detection, including for purposes of anti-money laundering and combating the financing of terrorism (AML/CFT); credit and insurance underwriting. AI can be particularly useful in high-frequency data analysis, creditworthiness assessment procedures, algorithmic trading, as well as other areas of risk management, including monitoring and detection of fraud or counterfeiting (OECD, 2021; OECD, 2023; FSB, 2024; OECD, 2024b).

Artificial intelligence (AI), like most technologies, can bring many benefits, but it can also create risks. Those possible ones in the use of AI relate mainly to cybersecurity (i.e., Aldasoro et al., 2024), and include micro prudential risks, such as credit risk, insurance risk, model risk, operational risks, reputational risks, conduct. Furthermore, there are the risks of AI consumer protection risks and macro risk. Additionally, AI generates macroprudential or financial stability risks. Its use may heighten existing risks, such as a model risk (e.g., the lack of explainability makes it challenging to assess the appropriateness of AI models) and data-related risks e.g., privacy, security, bias (see Crisanto et al., 2024).

AI contributes to strengthening the market power in digitized markets and raise new antitrust issues (for example, it affects competition in the sphere of innovation and will create a new space for collusive pricing or abuse of dominant positions). AI can facilitate collusion, lead to abuse of a dominant position, and reduce a competitive pressure, which creates many challenges for the existing competition policy regime OECD (2023).

Risks in the use of AI also relate to market concentration and distortions of competition (i.e., Gambacorta and Shreeti, 2025). Artificial intelligence is powered by huge amounts of data that require high computing power, and this leads to the risk of concentration on AI product providers to a few dominant companies (OECD, 2021). However, companies utilizing AI may be exposed to third-party risks, e.g., access to data is crucial for the effectiveness of models like LLM, the concentration of data suppliers, such as large technology companies (Big Tech) or other platforms.

According to Gambacorta and Shreeti (2025), a typical AI application consists of hardware, including graphic processors, cloud computing infrastructure, training data for models and AI applications. On the one hand, artificial intelligence requires more data and better hardware. Hardware, on the other hand, requires new sources of energy. Energy use of data centers depends on several parameters, such as the number of computer instances hosted per server, data centers' workloads, power usage effectiveness (processor efficiency and idle power management) or data center storage capacity (OECD, 2021).

The level of development of AI tools and the risk of reliability of the results are limitations in its use for decisions in the financial sector. Trust in artificial intelligence in banking is lower than in comparable sectors (i.e., Aldasoro et al., 2024). Due to fast development of AI, the European Council approved the AI Act, a regulation that addresses issues related to artificial intelligence (May 27, 2024). On August 1, 2024, twenty days after its publication in the EU Official Journal, the AI Act entered into force and is based on risk-based policy approaches and high-risk AI systems.

4. Description of the Model Based on Literature

In this section, the construction of an empirical model that examines the relationship between the bank credit and FinTech credit in European economies based on the literature is presented. However, due to limited availability of data on FinTech credit, the number of scientific studies remains relatively small.

Most of these studies examine the issue on a global scale or focus primarily on the economies of China and the United States. Nevertheless, research results regarding the role of FinTech credit in relation to bank credit or other forms of financing do not provide clear conclusions and yield different outcomes (e.g., Claessens et al., 2018; Tang, 2019; Bao & Huang, 2021; Cornelli et al., 2023). Claessens et al. (2018) found that FinTech credit is negatively correlated with competition in the banking market and the severity of regulation of that market. Furthermore, Tang (2019) found that in the United States, P2P lending is complement for bank lending with respect to small loans. Finally, Cornelli et al. (2023), using global data, found that Fintech and big tech credit complement rather than substitute traditional bank credit.

To answer the research question, we first describe the data and methods used in our empirical research and then present the results of the model. We use a panel regression model (Baltagi, 2005; Wooldridge, 2010), which was estimated with two techniques: pool regression, ordinary least squares (OLS) and panel regression fixed-effects estimator (FE).

4.1. Description of Variables

In order to provide quantitative research the panel data was constructed. The panel data included annual data at the national level for selected European economies. Data in the panel covers the macroeconomic situation (e.g., GDP growth) in individual European economies, the level of concentration in individual banking sectors, the bank performance, digitalization, FinTech companies, FinTech credit and a number of data centers as proxy of AI. Data for individual European countries was obtained from publicly available online databases of international organizations. Data on innovative technologies (including payment services) comes from the International Monetary Fund, the European Central Bank (Statistical Data Warehouse) and Eurostat (data on internet use and mobile telephony). Data concerning banking credit comes from the European Credit Research Institute (ECRI) at the Centre for European Policy Studies (CEPS).[1] Additionally, FinTech variables are from the studies: Cornelli et al. (2020), Cornelli et al. (2021) and AI data from Statista.[2] One limitation of the study is the limited availability of data on FinTech loans, as the publicly available dataset starts in 2013 and ends in 2019, and does not cover all the European Union countries. Due to the restricted data availability regarding FinTech credit, the panel includes data only for the following countries: Austria, Belgium, Bulgaria, the Czech Republic, Germany, Denmark, France, Estonia, Ireland, Spain, Finland, the United Kingdom, Italy, Lithuania, Latvia, the Netherlands, Poland, Portugal, Sweden, Slovakia and Slovenia. Due to a lack of data, the panel was unbalanced.

4.2. The Panel Linear Regression Model

To verify the research hypotheses, the econometric model was constructed based on the literature (i.e., Claessens et al., 2018; Cornelli et al., 2023). The baseline equation aims to examine the role of FinTech credit and digitalization on the credit market. However, the purpose of constructing the equation is to verify whether FinTech credit is a substitute for, or a complement to, bank loans. The equation in the model was estimated using panel data analysis techniques.[3]

Equation (1) represents the output specification of the constructed baseline econometric model based on panel data:

$$\Delta Y_{c,t} = \mu_t + \gamma_c + \alpha_1 MS_{c,t} + \alpha_2 BankL_{c,t} + \alpha_3 GDP_{c,t} + \alpha_4 ROAc,t + \alpha_5 RISKc,t + \alpha_6 DigTech_{c,t} + \alpha_7 FinTechc,t + \alpha_8 AI + \varepsilon_{c,t} \quad (1)$$

where the explained variable $Y_{c,t}$ is FinTech credit variables in country c in year *t*.

[1] The ECRI Statistical Package provides a comprehensive overview of the trends and composition of lending to non-financial corporations and households.

[2] Data center is a network of computing and storage resources that enables the delivery of shared software applications and data.

[3] The model was estimated based on panel data and cross-sectional data using the FE and OLS estimators.

The explanatory variables in the model are:

- $GDP_{c,t}$ defines the macroeconomic situation determined by the GDP growth rate yoy (*GDP*) in country *c* in year *t*;
- $MS_{c,t}$ as indicators of market structure: the share of the five largest credit institutions in total assets ($CR5_{c,t}$) and as the HHI for assets (the sum of the squares of the market share of individual banks[4]), for country *c* in year *t*;
- $BankL_{c,t}$ describes the grow of total loans to non-financial sector; loans for household, loans for corporates for country *c* in year *t*;
- $ROAc,t$ describes return on assts in the banking sector for country *c* in year *t*;
- $RISKc,t$ describes non-performing loans in the banking sector (*NPL*), for country *c* in year *t*;
- $DigTech$ describes the variables concerning the new technology *inside and outside* the banking sector (i.e., Pawłowska & Staniszewska, 2024) in country *c* in year *t*: *INTER* (people of using Internet as % of individuals), *ATM* (number of Automated Teller Machines [ATMs]; *ATM1* (number of Automated Teller Machines per 100 kk2); *MOB* (number of mobile phone subscriptions per 100 people), *card* (the number of payment cards) and *Server* (server number);
- *AI* describes us the number of data and AI centers[5] for country *c* in year *t*;
- $FinTech$ defines variables describing FinTech equity financing in relation to GDP ($FinTech$) for country c in year t; and value of the KFTX Stock Index[6] (*KFTX*) in year t.

Table 1 below presents the definition of variables for the model and summary statistics. In order to select appropriate variables for the model, the correlation between the variables was investigated.[7]

Kouretas and Pawłowska emphasize that the determinants of individual types of credit, which make up total credit, are different (i.e., Kouretas & Pawłowska, 2025). Therefore, additional equations were constructed to examine how the dynamics of various types of credit

[4] The Herfindahl-Hirschman Index (HHI) is calculated as the sum of the squares of each commercial bank's market share (e.g., in net assets). Index values range from 0 to 1, with higher index values indicating higher market concentration.

[5] A data center includes servers, storage systems, networking equipment, cooling systems, and security controls.

[6] KBW Nasdaq Financial Technology Index was created to track the capitalization of innovative companies in the financial sector. A company is included in the index if it provides digital solutions for the financial market (see: Pawłowska & Staniszewska, 2024).

[7] The Spearman's rank correlation between all variables in the model is estimated for the whole sample of model.

affect FinTech credit, divided into credit for households and for corporations. In order to check what the relationship between FinTech credit and credit for households as well as credit for corporates is, equation 2 was constructed. Equation (2) represents the output specification of the constructed econometric model based on panel data:

$$\Delta Y_{c,t} = \mu_t + \gamma_c + \alpha_1 MS_{c,t} + \alpha_{21} BankL\_H_{c,t} + \alpha_{22} BankL\_NFC_{c,t} + \alpha_3 GDP_{c,t} + \alpha_4 ROAc,t + \alpha_5 RISKc,t + \alpha_6 DigTech_{c,t} + \alpha_7 FinTechc,t + \alpha_8 AI + \varepsilon_{c,t} \quad (2)$$

where the explained variable $Y_{c,t}$ is FinTech credit variables in country c in year *t*.

The explanatory variables in the model are:

- $BankLH_{c,t}$ describes the growth of loans for household (L_H) for country *c* in year t;
- $BankLNFC_{c,t}$ describes the growth of loans for corporates (L_NFC) for country *c* in year t.

The remaining explanatory variables are the same as in equation (1).

Based on equation (1), six estimates were made regarding the determinants of FinTech credit: three using the OLS estimator and three using panel data regression (FE). All estimations in the models are estimated separately to avoid any alignment of variables. Table 2 presents the results of the panel regressions coefficients.

In Table 2 the positive and insignificant coefficient α_2 was found for total loans (columns 1, 2, 3, 4, 5, 6). Of course, the variables determining digital technologies had a significant impact on the growth of FinTech credit. However, only, the positive and significant coefficient α_6 was found for the explained variable *INTER* (columns 2 and 5) and Server (column 4). These results suggest that digitalization had a positive impact on FinTech credit in European countries. Interestingly, the concentration (*CR5*) and profitability of banks (*ROA*) proved to be significant and positive for FinTech credit. This result may suggest that lower competition in the banking sector positively affects the attractiveness of alternative sources of financing and FinTech credit. Furthermore, variable *NPL* was significant and negative for FinTech credit. It may mean that a greater credit risk in the banking sector increased a FinTech credit. Finally, AI has a positive impact on FinTech credit (columns 2, 3, 5, 6).

Additional six estimations were made based on equation 2, three using the OLS estimator and three using panel data regression with Fixed Effects (FE). Table 3 presents the results of the tree linear regressions OLS and tree for panel regression FE. In Table 3, the negative and significant coefficient α_{21} was found for loans for household (i.e., columns 1, 3, 4, 5, 6) and the positive and insignificant coefficient α_{22} was found for loans for corporates (columns 1, 2, 3, 5, 6) and the positive and significant in column 4. Like in model 1, only the positive and significant coefficient α_6 was found for the explained variable *INTER* (columns 2 and 5) and Server (columns 1, 3 and 5, 6). Also, concentration (*CR5*) and profitability of banks (*ROA*) proved to be significant and positive for FinTech credit. Furthermore, variable NPL was significant and negative for a FinTech credit. Finally, AI has a positive impact on a FinTech credit (columns 2, 4, 5).

Certainly, the *FinTech* variable had a positive and significant impact on the growth of FinTech credit (Tables 2 and 3).

Table 1

Construction of variables for model and summary statistics of selected European countries

Variable names	Definitions	Nu. of Obs.	Mean	Std. Dev.	MIN	MAX
Banking Variables						
CR5	Share of the 5 largest credit institutions in total assets	196	62.462	18.20	26.18	97.35
HHI	Herfindahl-Hirschman for assets	196	0.1365	0.15673	0.0245	1.3
ROA	Return on assets	196	0.4896	0.78286	−2.55	3.04
ROE	Return on equity	185	3.961	15.7455	−145.53	21.53
NPL	Non-performing loans	193	8.028	9.602	.2131	46.78
Credit Variables						
T_Loans	% annual change in total loans	196	0.0052	0.0979	−0.4384	0.6125
L_H	% annual change in credit for household	196	0.027558	0.06671	−0.3331	0.25603
L_NFC	% annual change in credit for nonfinancial corporation	196	−.0020976	0.07280	−0.2630	0.3102
FinTech Variables						
*FinC***	FinTech credit to GDP	147	13329.09	18448.5	0	46054
*FinTechC***	% annual change in FinTech credit	138	5.6669	5.166	−4.60	5.006
*FinTech**	Fintech equity funding in relation to GDP	175	0.1068	0.4681	0	6.694
KFTX	The value of the KFTX Stock Index	196	1128.053	231.64	849	1434
Economic Growth Variables						
GDP	The gross domestic product growth rate Yoy	196	2.975	2.78129	−1.4	25.1
DigTech Variables						
ATM	Number of Automated Teller Machines (ATMs)	147	14818.11	32002.9	211	86702

Variable names	Definitions	Nu. of Obs.	Mean	Std. Dev.	MIN	MAX
ATM1	Number of Automated Teller Machines per 100 kk2 (ATMs)	147	120.857	132.4635	4.79	687.5
Card	Logarithm of number of credit card	150	1.2384	0.815	0.6632	10.477
INTER	Individuals using the Internet (%)	144	81.833	8.9161	59.5	98.14
MOB	Number of mobile phone subscriptions per 100 people	147	123.5011	15.625	99.45	168.82
Server	Logarithm of number of secure servers	167	9.777	1.2048	4.755	12.532
AI Variable						
AI	Logarithm of Number of data centers	168	3.51941	2.3025	1.4272	6.2709

**Data from studies: Cornelli et al., 2020. * Data from Cornelli et al., 2021, pp. 31–43.

Source: Own calculation based on publicly available online databases of international organizations, such as the World Bank, International Monetary Fund, European Central Bank (Statistical Data Warehouse), Eurostat, Bloomberg. Data concerning credit is from European Credit Research Institute (ECRI) at the Centre for European Policy Studies (CEPS) for banking sectors form Statistical Package 2022, AI variables from Statista.

Table 2

Empirical Results for equation 1

	FinTechC	FinTechC	FinTechC	FinTechC	FinTechC	FinTechC
Variable name	1	2	3	4	5	6
	OLS	OLS	OLS	FE	FE	FE
T_Loans	0.020	0.047	0.017	0.072	0.081	0.020
	(0.055)	(0.056)	(0.055)	(0.057)	(0.060)	(0.055)
CR5	0.069*	0.080**	0.072**	0.414**	0.309*	0.069*
	(0.035)	(0.033)	(0.033)	(0.172)	(0.168)	(0.035)
ROA	1.255	2.997***	1.776	−0.162	1.858	1.255
	(1.169)	(1.133)	(1.193)	(1.492)	(1.561)	(1.169)
NPL	−0.401***	—	−0.319**	−0.798***	—	−0.401***
	(0.122)	—	(0.123)	(0.236)	—	(0.122)
GDP	11.707**	7.114	9.571*	8.780	6.495	9.647*
	(5.617)	(5.872)	(5.577)	(5.633)	(6.145)	(5.616)
MOB	−3.500	−0.874	−3.443	−14.916	9.060	0.051
	(5.076)	(4.638)	(4.575)	(12.436)	(10.610)	(11.019)
Server	0.057	0.041	0.032	0.131*	0.058	0.054
	(0.057)	(0.059)	(0.056)	(0.067)	(0.059)	(0.061)

Variable name	FinTechC 1 OLS	FinTechC 2 OLS	FinTechC 3 OLS	FinTechC 4 FE	FinTechC 5 FE	FinTechC 6 FE
Card	0.323	—	—	0.305	—	—
	(1.823)	—	—	(1.842)	—	—
FinTech	0.663	—	—	0.654	—	—
	(0.872)	—	—	(0.880)	—	—
AI	0.849	1.419**	1.201**	0.857	1.350**	2.986*
	(0.846)	(0.551)	(0.536)	(0.855)	(0.633)	(0.139)
ATM	—	−0.003	0.002	—	−0.003	−0.030
	—	(0.007)	(0.007)	—	(0.008)	(0.045)
INTER	—	0.151**	—	—	0.208*	—
	—	(0.063)	—	—	(0.106)	—
KTFX	—	4.727**	0.805	—	4.165*	0.100
	—	(2.194)	(2.487)	—	(2.182)	(3.897)
Obser.	101	103	104	101	103	104
ID	0.588	0.535	0.573	0.619	0.453	0.446
R-squared	—	—	—	21	21	21

*** p < 0.01, ** p < 0.05, * p < 0.1. Standard errors in parentheses.

Source: Own calculation.

Table 3

Empirical Results for equation 1

Variable name	FinTechC 1 OLS	FinTechC 2 OLS	FinTechC 3 OLS	FinTechC 4 FE	FinTechC 5 FE	FinTechC 6 FE
L_H	−0.264**	−0.194	−0.359**	−0.286**	−0.212	−0.264**
	(0.127)	(0.158)	(0.147)	(0.123)	(0.158)	(0.127)
L_NFC	0.106	0.049	0.057	0.115*	0.055	0.106
	(0.071)	(0.074)	(0.067)	(0.069)	(0.074)	(0.071)
CR5	0.074**	0.079**	0.073**	0.078*	0.079**	0.074**
	(0.034)	(0.034)	(0.032)	(0.041)	(0.036)	(0.034)
ROA	1.187	3.122***	2.043*	0.960	3.078**	1.187
	(1.150)	(1.180)	(1.179)	(1.196)	(1.206)	(1.150)

Variable name	FinTechC	FinTechC	FinTechC	FinTechC	FinTechC	FinTechC
	1	2	3	4	5	6
	OLS	OLS	OLS	FE	FE	FE
NPL	−0.389***	—	−0.304**	−0.426***	—	−0.389***
	(0.119)	—	(0.120)	(0.133)	—	(0.119)
GDP	8.694	5.937	7.648	8.814	6.369	7.901
	(5.661)	(6.200)	(5.784)	(5.606)	(5.932)	(5.746)
MOB	−3.336	−0.401	−2.602	−3.394	0.453	−2.472
	(4.918)	(4.652)	(4.428)	(5.061)	(5.367)	(4.522)
Server	0.886**	—	1.037***	0.944**	—	1.042***
	(0.352)	—	(0.312)	(0.367)	—	(0.314)
Card	−0.117	—	—	1.179	—	—
	(1.766)	—	—	(2.041)	—	—
FinTech	0.820	—	—	2.042**	—	—
	(0.724)	—	—	(0.798)	—	—
AI	0.868	1.371**	1.017*	−0.504	1.256*	1.003*
	(0.806)	(0.545)	(0.518)	(0.843)	(0.667)	(0.532)
ATM	—	−0.002	0.004	—	−0.003	0.004
	—	(0.007)	(0.007)	—	(0.009)	(0.007)
INTER	—	0.164**	—	—	0.184*	—
	—	(0.081)	—	—	(0.095)	—
KTFX	—	3.586**	1.765	—	3.529**	1.535
	—	(1.544)	(1.522)	—	(1.529)	(1.502)
Obser.	101	103	104	101	103	104
ID	—	—	—	21	21	21
R-squared	0.560	0.565	0.561	0.633	0.610	0.668

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses.

Source: Own calculation.

Moreover, we performed the robustness check based on equations 1 and 2 (see Table 4). In order to conduct the robustness tests first, we used a different approach to measure concentrations, second, we used a different approach to measuring digital technology and bank profitability. Finally, we estimated the baseline econometric model to be robust with using the *HHI* and *ROE* instead of *CR5* and *ROA*. Additionally, in the model we used *ATM1* as the DigiTech. Other dependent variables were defined in the same manner as in the baseline model. Table 4 presents the results of the panel regressions using equations 1 and 2 for the six estimates using the OLS estimator and panel data regression (FE).

Table 4

Empirical Results for equations 1 and 2

	FinTechC	FinTechC	FinTechC	FinTechC	FinTechC	FinTechC
Variable name	**1**	**2**	**3**	**4**	**5**	**6**
	OLS	**FE**	**FE**	**OLS**	**FE**	**FE**
L_H	—	—	—	−0.219	−0.537***	−0.523***
	—	—	—	(0.148)	(0.155)	(0.154)
L_NFC	—	—	—	0.161	0.086	0.096
	—	—	—	(0.101)	(0.075)	(0.074)
T_Loans	0.044	0.032	0.029	—	—	—
	(0.058)	(0.056)	(0.061)	—	—	—
HHI	23.583**	23.680	29.500	24.331**	28.540	29.640
	(10.228)	(25.805)	(38.460)	(11.391)	(23.822)	(23.722)
ROE	0.200**	0.076	−0.044	0.171	0.090	0.087
	(0.097)	(0.111)	(0.115)	(0.113)	(0.108)	(0.107)
NPL	−0.382***	−0.962***	−1.022***	−0.379***	−1.118***	−1.021***
	(0.135)	(0.354)	(0.292)	(0.140)	(0.329)	(0.322)
GDP	5.765	8.983	0.063	7.760	1.109	1.217
	(6.019)	(5.889)	(6.107)	(6.200)	(5.990)	(5.836)
MOB	−5.537	—	3.985	−4.329	—	8.344
	(5.165)	—	(9.555)	(5.132)	—	(8.911)
Server	0.852	—	0.073	1.671***	—	1.640***
	(0.562)	—	(0.617)	(0.492)	—	(0.447)
Card	−0.117	—	—	1.179	—	—
	(1.766)	—	—	(2.041)	—	—
FinTech	0.952	—	—	1.062*	—	—
	(0.658)	—	—	(0.635)	—	—
AI	0.796	1.371**	—	17.314*	16.673*	—
	(0.752)	(0.545)	—	(9.8675)	(9.8350)	—
ATM1	−0.597	—	—	−0.331	−0.597	—
	(0.440)	—	—	(0.436)	(0.440)	—
INTER	0.176*	0.869***	—	0.621**	0.665***	0.176*
	(0.103)	(0.242)	—	(0.260)	(0.232)	(0.103)
KTFX	—	4.459	—	—	3.856	4.086
	—	(4.738)	(3.210)	—	(4.322)	(4.046)
Obser.	101	96	96	96	91	91
ID	—	21	21	—	21	21
R−squared	0.441	0.582	0.547	0.507	0.676	0.647

Source: Own calculation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses.

The robustness check results generally confirmed the results of the baseline specification and the conclusions drawn from Tables 2–3. In Table 4, the positive and insignificant coefficient α_2 was found for total loans (columns 1, 2, 3). Furthermore, Table 4 shows the negative and significant coefficient α_{21} for loans for household (i.e., columns 5, 6) and the positive and insignificant coefficient α_{22} was found for loans for corporates (columns 4, 5, 6).

4.3. Summary of the Model Results

The model estimation results showed that in the case of model 1, it is not possible to clearly determine whether FinTech credit is a substitute or a complement to total credit. Estimating the model using equation 1 did not allow for an unambiguous verification of hypothesis 2. Therefore, six additional estimations were conducted for two different types of loans: loans for households and for corporates based on equation 2. The estimation results showed that FinTech credit seems to be a substitute for household loans. Furthermore, the robustness check results generally confirmed the results of the baseline specification. Interestingly, concentration (CR5) and bank profitability (ROA) proved to be significant for FinTech credit. On the one hand, the positive CR5 coefficient suggests that the higher the concentration in the banking sector and the lower the competition, the more FinTech credit tends to increase. This result may indicate that lower competition in the banking sector increases the attractiveness of alternative financing sources, including FinTech credit. AI support appears to foster the growth of FinTech credit. Furthermore, credit risk in the banking sector had a negative and significant impact on FinTech credit. Moreover, the analysis of the relevant literature and available studies indicated a significant impact of digital technologies on traditional banks and the entire financial sector. These changes are further driven using artificial intelligence. The above results allow us to conclude that digitalization has an impact on financial risk and traditional banks' performance.

Finally, the paper confirms the significant role of AI and FinTech companies in shaping traditional banks performance and credit market conditions, which impact the relationship between the financial sector and the real economy in European countries. However, the above results do not provide a clear answer to the research questions. These findings should be interpreted with caution due to significant data gaps. Therefore, further and more detailed research should be conducted based on a new data set.

5. Concluding Remarks

The paper analyses the impact of AI and FinTech on macro-financial linkages. The rapid development of artificial intelligence and digitalization in financial sector is taking place thanks to modern IT tools for storing huge amounts of data in the form of computing cloud and the possibility to process them, thanks to the increased power of computer and graphics processors. The above changes affect the financing of the real sector as well as the relationship between the financial sector and the real sphere of the economy. Furthermore, in today's world, technological progress is accelerating, which means that the concept of artificial intelligence is constantly evolving and changing.

The paper finds that digitalization affects bank performance and financial risk in European countries. Additionally, using a panel data regression model it shows that in European countries, especially those within the EU, FinTech credit tends to substitute household credit rather than complement bank credit, while total credit seems to be complementary. These results differ slightly from those of Cornelli, Frost, Gambacorta, Rau, Wardrop, and Ziegler (2023), who, based on a global database of FinTech and BigTech lending, found that FinTech and BigTech credit tend to complement rather than substitute other forms of credit. However, it should be noted that FinTech and BigTech companies are developing mainly in Asia. In European countries, traditional banks still dominate the financial sector; nevertheless, they continue to invest in new technologies and adopt additional distribution channels.

Although many reports have been prepared by financial institutions, there is still a lack of empirical research on the impact of new technologies on the bank loan market in European banking sector. The novelty of this paper lies in its analysis of these phenomena in Europe, mainly in the EU countries, which contributes to the literature on the subject. The practical implications of this paper offer valuable insights into macroprudential policy in the EU. However, the limitation of the study is the availability of data on FinTech credit, which ended in 2019. Further research should be conducted on an expanded panel of data concerning FinTech credit and the use of AI in banks.

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